Synopsis

Ph.D in Computer Science

Modified Extreme Learning Machine Algorithm with Deterministic Weight Modification for Investment Decisions Based on Sentiment Analysis

By

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I. Introduction

State of the Art

A significant problem in the topic of economics is stock market prediction. Due to the noise and volatility, however, timely prediction is typically regarded as one of the most difficult challenges. A sentiment-based stock price prediction that takes investors' emotional trends into account to overcome these difficulties. Hence, this article presents a new sentiment analysis based-stock prediction method using a modified extreme learning machine (ELM) with deterministic weight modification (DWM) called S-DELM. First, investor sentiment is used in stock prediction, which can considerably increase the model's predictive power. Hence, a convolutional neural network (CNN) is used to classify the user comments. Second, DWM is applied to optimize the weights and biases of ELM. Enhancing ELM's generalization performance and prediction accuracy are the aim of the study endeavor. The results of the experiments demonstrate that the S-DELM may not only increase prediction accuracy but also shorten prediction time and Investors' emotional tendencies are proven to help them achieve the expected results. The performance of S-DELM is compared with different variants of ELM and some conventional method.

II. Motivation

To increase profits, a lot of people and organizations make stock market predictions. Investors can make well-informed judgments on when to purchase, sell, or hold stocks to produce returns on their investments by properly forecasting the movement of stock prices. Investor risk management can also be aided bystock market prediction. Investors can modify their portfolios to reduce losses and protect wealth byseeing impending market downturns or spotting cheap equities. Access to and analysis of a wide range of data, such as financial reports, economic indicators, news items, and market sentiment, are necessary for successful stock market prediction. A competitive edge in the market is gained by those who can efficiently obtain and analyze this data. The use of algorithmic trading has grown in popularity as technology has progressed. Algorithms are made to evaluate market data and automatically carry out trades according to pre-established standards. Predicting the stock market is essential to the creation and improvement of these algorithms.

This thesis's primary goal is to investigate how the opinions expressed in online news stories about financial firms that are listed on the stock market affect the movement of stock prices.An algorithm for a prediction system would be created based on this correlation between news stories and stock values. The overall goal of this effort is to give investors in

the online environment predictive capacity so they can decide for themselves whether or not to invest in the firm in question and hope to make large profits.

III. Problem Definition

The stock market's volatility and complexity make it difficult to predict and analyze its key drivers. Creating models that forecast stock price fluctuations, both short-term and long-term, is a tough issue. Many people believe that investing in the stock market is dangerous due to the various elements that influence share values. The stock market might lead to higher losses for investors due to its inherent risk. Decisions about investments are greatly influenced by one's awareness of the dangers and different external factors. A vital source for stock market investing is the market's information, news, advice, and sentiments. Hence, the present study entitled "**Modified Extreme Learning machine Algorithm with Deterministic Weight modification for Investment Decisions Based on Sentiment Analysis"** is taken up.

IV.Objectives of the Research

The study has the following objectives:

1) Understand the various approaches used in the stock price forecast.

2) Examine selected appropriate strategies to learn whether the strategies predicted the same closing price indication or not.

3) Revise Extreme machine learning and merge sentimental models for making investment decisions in stock markets.

V.Review of Literature

Literature reviews play a significant role in the development and advancement of stock market prediction research.Reviews of the literature give a summary of the approaches, results, and studies that have already been done on stock market prediction. Researchers get a greater grasp of the most advanced methods and strategies in the field by combining the insights from earlier studies.The Table 1 shows some recent research work focused on stock market predictions.

Table1:Related works

S. No	YEAR	AUTHORS	TITLE OFPAPER	REMARKS
1	2016	X.Lietal.	Empirical analysis:stock Market prediction via ELM	The stock closing price is predicted by ELM
2	2022	S.Daset al.	Stock market forecasting using intrinsic time-scale decomposition in fusion withcluster-basedmodified CSA-optimizedELM	By improving the Crow SearchAlgorithm (CSA) to choose the ideal weight and ELM biases,the CMCSA is proposed.
3	2021	D.Wuetal.	A hybrid method based on extreme learning machine and wavelet transform denoisingforstock Prediction	A denoising technique that combines DWT and ELM to forecast stock trends
4	2020	M.Vochozka et al.	Innovations in management forecast:Time development of stock prices with neural networks	Aims to innovate prediction management by using neural networks to predict the evolution of share Prices over time.
5	2018	H.Huet al.	Predicting the direction of stock markets using optimized neural networks with Google Trends	Enhances the sine cosine algorithm (SCA)by adding a new parameter to improve the BPNN's weights and bias.
6	2020	Z.Jin et al.	Stock closing price prediction based on sentiment analysis and LSTM	DL-based stock market forecasting model thattakes the emotional inclinations of investors into account

7	2019	A. Derakhshan et al.	Sentiment analysis on stock social media for stock price movement prediction	challenge of model-based opinion mining by utilizing a graphical part-of-speech model to extract user sentiments
8	2021	D. Mohanty	Financial market prediction under deep learning framework using an autoencoder and kernel Extreme learning machine	The KELM and stacked AE are combined to predict various bank data.
9	2021	D.Wuetal.	A hybrid method based on extreme learning machine and wavelet transform denoising for stock Prediction	Suggested using DWT and ELM-based denoising in tandem to forecast stock trend
10	2020	S.C. Nayak	Extreme learning with chemical reaction optimization for stock volatility prediction	It creates a learning framework known as "extreme learning with chemical reaction optimization" that combinesthebenefitsof ELM and CRO.
11	2020	P. Khuwaja	Prediction of stock movement using phase space reconstruction and Extreme learning machines	A system that uses phase space reconstruction (PSR) and ELM to forecast changes in stock prices.
12	2023	Balakrishnan S	Empirical Evaluation of Stock Market Forecasting via Extreme Learning Machine	Aims to provide a DL that uses bottom NN models and empirical mode deconstruction to automatically mine the statistic laws of material And guide stockmarket operations.

VI.Methodology

The present research work used three research methods are considered such as ELM, deterministic weight modification (DWM), and convolutional neural network (CNN).

Phase-1

The ELM approach computes the output weights of SLFNs analytically and first initializes hidden node values at random.The main advantage of ELM is that the buried layer of SLFNs doesn't need to be tuned.For the randomly chosen input weights and hidden layer biases, ELM will produce the least squares solution of a system of linear equations for the unknown output weights with the minimum norm property.For numerous real-world applications, ELM has shown good generalization results with a very fast learning rate [5-8]. Nevertheless, there are still a lot of issues with the actual application of the ELM. The most important one is the selection of the optimal hyperparameters such as the number of hidden nodes, connection weights and biases, and learning rate which are usually done by trial and error.Generally speaking, the ELM requires more hidden neurons than more conventional tuning-based learning methods.As a result, a lot of studies have been done to determine the best weights and biases for ELM to improve prediction outcomes.However, there are numerous flaws in the standard methods, including local optima, a lengthy computation time, and a low convergence rate.Therefore, the weight and bias of the ELM known as DELM, which was applied to stock price prediction, were adjusted using DWM.When the DELM was compared to some conventional and variant ELMs, the accuracy result was greater. Further, the historical datasets are considered such as open price, high price, low price, closing price, and adjusted close in this phase for stock price prediction.

Phase-2

It is frequently difficult to discern important patterns from random variations in historical pricing data due to the high noise content. Erroneous trading decisions might result from traders misinterpreting noise as noteworthy trends or patterns.Technical indicators offer valuable information about market patterns, price movements, and possible future price directions, which is useful when examining stock market data.Technical indicators are useful for verifying market trends or price changes.Price and indicator moves that diverge could indicate future market reversals or continuations.It helps with risk management by offering information about possible gains or losses.Technical indicators are useful instruments for analyzing the market, but to make informed trading decisions, they should be combined with other types of analysis, such as fundamental analysis.Hence, the second phase of research work uses the ten different technical indicators such as Simple Moving Average (SMV), 10-

day Moving Average, Momentum, Stochastic (K%), Stochastic (D%), Relative Strength Index (RSI), Williams (%R), Moving Average Convergence Divergence (MACD), Commodity Channel Index (CCI), Price Oscillator (PO) are used for predicting stock price using DWM-ELM.

Phase-3

Conversely, the developed stock market prediction algorithms ignore other factors that affect stocks and their complex internal workings in favor of primarily using historical data as their input.Because people are inconsistent, the stock market does not always operate according to systematic rules.Their behavioral, psychological, and emotional characteristics are vital in the economic system.Furthermore, new research has shown that investor attitude may have a significant impact on stock market returns.There is a stronghint that investors are not irrational, and as social networks become more important in people's lives, shareholder connections in the stock market are getting easier and more common.

Thus, an investor's perspective and decision-making procedures maybe influenced bythe feelings and opinions of other investors as well as those shared on social media.Next, the CNN technique is used to extract the user comments. The suggested plan considers investor sentiment by computing binary sentiment indices for optimistic and negative sentiments.An algorithm for sentiment analys is based on CNN that divides stock market remarks in to bullish and negative perspectives.Next, the stock price that is improved by DWM is predicted using enhanced ELM .Finally, technical indicators and user comments datasets are considered as inputs to the prediction method.The developed sentiment-based DWM-ELM called S-DELM is applied to predict the stock market price.Algorithm 1 and Figure 1 show the proposed sentiment-based DELM method.Finally, the use of technical indicators, optimal hyperparameters optimization, and customer sentiment are considered in the proposed research work for achieving the following remarkable objectives such as reducing prediction error, enhancing prediction accuracy, and making fast learning time and fast convergencerate.Further, some of the following remarkable points are short definitions of the contribution of the research work, The sentiment-based optimized ELM is applied to predict the stock price.

- To determine user sentiment on the stock,a CNN-based classification algorithmis used to calculate the sentiment index (SI).
- To identify factors affecting the share market with stockholder sentiment analysis or classification of opinion sentiment into bullish or bearish.
- To produce sentiment analysisin real-time that can forecast the value of the stock

market and, using historical data, estimate the approximate share price.

- The DWM method is used to optimize the weights and bias of ELM toenhance theperformance ELM method.
- Six stockmarket datasets are used to analyze the performance of S-DELM
- Different performance analyzers are considered for analyzing the strength of the S-DELM method

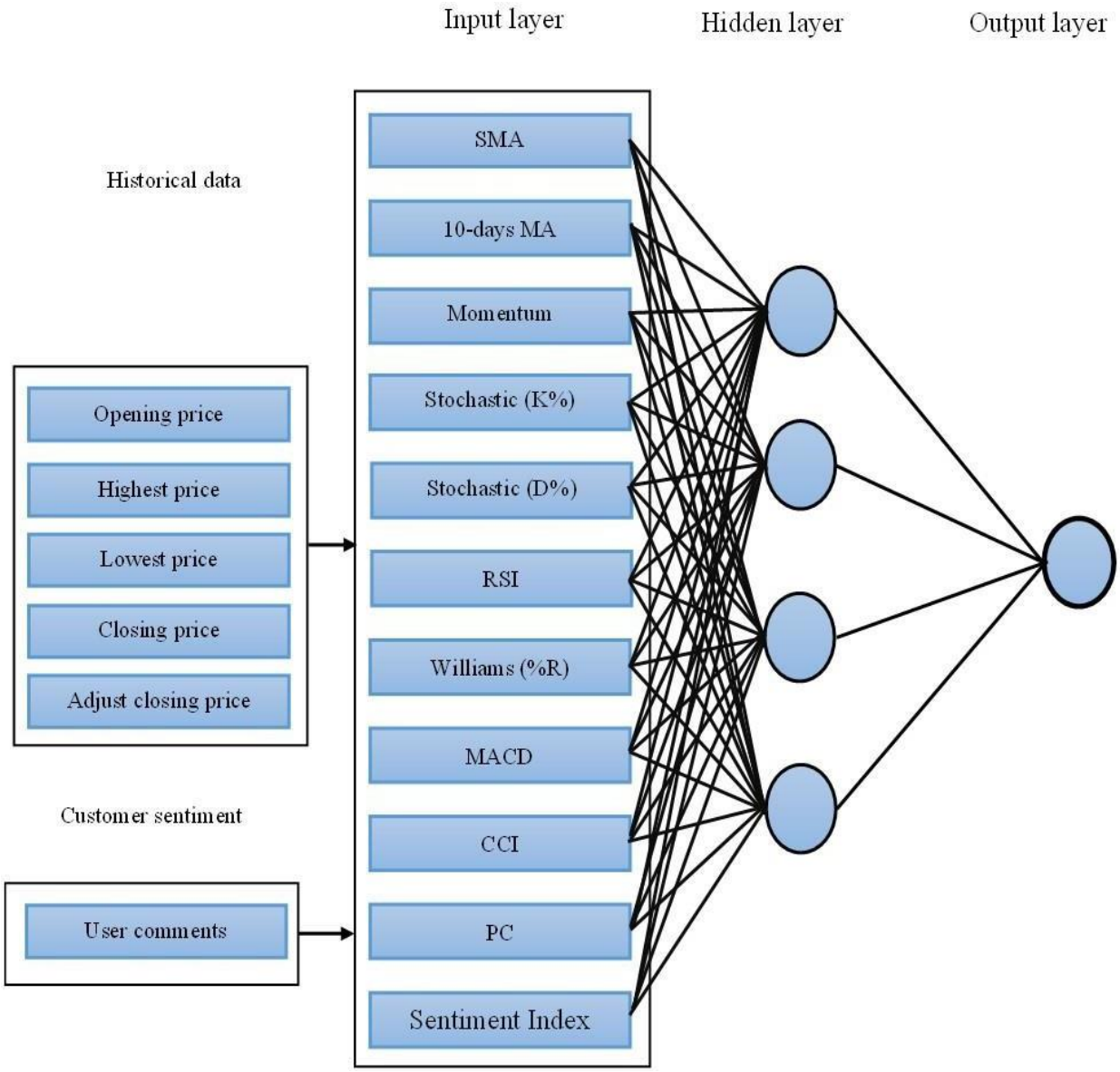

Figure1:Architectureof proposed method

Experimental Results

Using a collection of common stock datasets, this section evaluates the suggested sentiment-based DELM's capacity to predict future prices.

Datasets

Two different experimental datasets are gathered, including the historical data and the comment dataset that calculates the SI.The stock market closing price is considered as a prediction value.In this research work, three phases of work are carried out to achieve the optimum prediction results.The stock market closing price is considered as a prediction value.The closing price is considered as target a value that is compared with output valuesof the neural networks.

Historical datasets

Stock exchanges, market data providers, financial data suppliers, and research platforms are frequently the sources of these historical statistics. They can be applied to several different tasks,such as machine learning-based prediction models,algorithmic trading, quantitative, technical, and fundamental analysis. Ensuring the quality, accuracy, and completeness of data is crucial when utilizing historical information for analytical and research purposes.In terms of historical data, we choose five features, including the opening prices, the highest price, the lowest price, the closing price, and the adjusted closing price. Two stock indices are the S&P BSE Sensex and the Nifty 50.Two significant stock exchanges in India are the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE).

There are several relationships and dependencies even if they both work in the same financial ecosystem.State Bank of India (SBIN), ICICI Bank (ICICI), and HDFC Bank are two Indian stock bank prices.SBIN,ICICI, and HDFC Bank all belong to the banking sector. They are subject to similar regulatory environments, economic conditions, and market trends that affect the banking industry as a whole.Also, Microsoft datasets were collectedt hat were retrieved from Yahoo .Microsoft is a company in the technology industry and is impacted by a variety of wider technological trends, such as improvements in software development, cloud computing, artificial intelligence, and cybersecurity.The focus of short- term analysis is on stock rmarket price movements that occur immediately or shortly,

frequently in a matter of days, weeks, or months. Long-term analysis examines the general patterns and performance of the market or equities over protracted timeframes, usually years

or decades.Datasets between March 2013-2014 to March 2022-2023 (10 financial years) are included (10 years).3247 trading days dataset samples are (2435) and 30% (812).

Stock user comments

The stock comment dataset includes comments for model training and a final comment that needs to be classified to find the SI.First, the model was trained using stock holder comments posted on StockTwits"(https://stocktwits.com/)". It is up to investors to mark a comment as bullish or bearish, even if StockTwits is a well-known public depositor site.This allows for the collection of a large number of incredibly accurate remarks.We crawl the 96,903 comments on the site for training reasons.Twenty-five companies' worth of data spanning nearly a decade is available on StockTwits. Among the companies were Visa, Tesla,Adobe,Apple, and so on.The stock symbol, message, date, time, message ID, and user ID for each communication are contained in the corresponding file .Dependencies between stocks in the same sector or business can be attributed to similar market conditions, economic trends, regulatory effects, and industry-specific events. Technology equities, for instance, could be impacted by comparable technologies.

Performance measures

The accuracy and efficacy of stock market prediction models in predicting futurestock prices or trends are evaluated through performance criteria.Performance indicators offer important information about how robust, accurate, and reliable stock market prediction algorithms are.To fully assess model performance, many indicators may be utilized in combination or prioritized based on the particular goals and specifications of the prediction task.The performance is measured with four methods namely Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-Square (R ^2) which are determined as follows,

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}|$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

Where,

$\hat{y}$ $-$ *predicted value of* y

$\bar{y}$ $-$ *mean value of* y

Result analysis

Analyzing stock market prediction results entails assessing predictive model performance, analyzing the results, and drawing practical conclusions.The present research work focused on various performance evaluations conducted for evaluating the performance of developed stock market prediction methods such as training and testing, convergence analysis, and predicted values with actual stock closing prices.

Result analysis: Phase -I

Phase 1 uses the DELM for predicting the stock market price which uses historical features such as opening, low, high, closing, and adjusted closingprices for inputs to the DELM.The DWM method is used to connect weights and bias of ELM for enhancing the performance.The present sub-section discusses the ability of the developed DELM method.Tables 3, 5 ,7, 9, and 11 shows the training performance of MSE,RMSE,MAE,MAPE,andR-Squarevalues ,respectively.Tables 4,6,8,10,and12 shows the testing performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively.

Table3:TrainingPerformanceComparisonsforMSE

Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.00074	0.000843	0.001291	0.00482	0.006293	0.009061
Nifty 50	0.00013	0.001365	0.001517	0.001738	0.001995	0.002155
SBIN	0.00088	0.000937	0.001045	0.001591	0.001836	0.002067
ICICI	0.00076	0.000863	0.000983	0.001135	0.001455	0.001864
HDFC	0.00069	0.000821	0.000973	0.001847	0.002851	0.003195
MSFT	0.00065	0.000694	0.000792	0.000984	0.001587	0.001918

Table4:TestingPerformanceComparisonsforMSE

Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.00105	0.00122	0.00294	0.00346	0.00598	0.00718
Nifty 50	0.00582	0.00768	0.00892	0.01029	0.01529	0.01989
SBIN	0.00068	0.00087	0.00094	0.00119	0.0014	0.00176
ICICI	0.00048	0.00066	0.00089	0.00122	0.00143	0.00185
HDFC	0.00059	0.0008	0.00093	0.00119	0.00135	0.0017
MSFT	0.00061	0.00695	0.00749	0.00897	0.01099	0.0201

Table5:TrainingPerformanceComparisonsforRMSE

Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.02716	0.02903	0.03593	0.06942	0.07932	0.09518
Nifty 50	0.01135	0.03694	0.03894	0.04168	0.04466	0.04642
SBIN	0.02958	0.03061	0.03232	0.03988	0.04284	0.04546
ICICI	0.02753	0.02937	0.03135	0.03368	0.03814	0.04317
HDFC	0.02628	0.02865	0.03119	0.04297	0.05339	0.05652
MSFT	0.02555	0.02634	0.02814	0.03136	0.03983	0.04379

Table6:TestingperformancecomparisonsforRMSE

Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.0324	0.03492	0.05422	0.05882	0.07733	0.08473
Nifty 50	0.07628	0.08763	0.09444	0.10144	0.12365	0.14103
SBIN	0.02607	0.02941	0.03069	0.03451	0.03735	0.04194
ICICI	0.0219	0.02565	0.02988	0.03494	0.03776	0.04303
HDFC	0.02429	0.02824	0.03051	0.03455	0.03677	0.0412
MSFT	0.02469	0.08336	0.08654	0.09471	0.10483	0.14177

Table7:TrainingPerformancecomparisonsforMAE						
Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.0079	0.0095	0.0106	0.0381	0.0451	0.0621
Nifty 50	0.0084	0.0092	0.0192	0.0281	0.041	0.0515
SBIN	0.0051	0.0059	0.00631	0.0072	0.0095	0.0103
ICICI	0.0058	0.0069	0.0081	0.0172	0.0377	0.0412
HDFC	0.0063	0.0072	0.0079	0.0085	0.0093	0.01016
MSFT	0.0067	0.0075	0.0084	0.0095	0.0101	0.0115

Table8:TestingPerformancecomparisonsforMAE						
Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.0102	0.0106	0.0119	0.0125	0.0141	0.0152
Nifty 50	0.0752	0.0886	0.0938	0.1022	0.1256	0.1495
SBIN	0.0119	0.0124	0.0142	0.0172	0.0199	0.0208
ICICI	0.0122	0.0153	0.0291	0.0315	0.0515	0.0821
HDFC	0.0138	0.0145	0.0156	0.0176	0.0181	0.0201
MSFT	0.0143	0.0127	0.0372	0.0511	0.0676	0.0859

Table9:TrainingperformancecomparisonsforMAPE						
Methods	DELM-T	GAELM	KELM	ELM	SVM	BPNN
S &P	0.0024	0.0035	0.0059	0.0069	0.0088	0.0105
Nifty 50	0.0079	0.0092	0.0102	0.0221	0.0281	0.0315
SBIN	0.0046	0.0056	0.0064	0.0071	0.009	0.011
ICICI	0.0008	0.0009	0.0018	0.0026	0.0039	0.009
HDFC	0.0057	0.0068	0.0072	0.0079	0.0094	0.0101
MSFT	0.0059	0.0063	0.0071	0.0078	0.0099	0.0105

Table10:TestingperformancecomparisonsforMAPE						
Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.0068	0.0072	0.008	0.0086	0.0098	0.0095
Nifty 50	0.0053	0.0065	0.0078	0.0086	0.0094	0.0105
SBIN	0.0031	0.0035	0.0051	0.0072	0.0099	0.0109
ICICI	0.0037	0.0041	0.0067	0.0098	0.0139	0.0193
HDFC	0.0039	0.0055	0.0069	0.0081	0.0095	0.0111
MSFT	0.0061	0.0065	0.0076	0.0081	0.0095	0.0112

Table11:TrainingperformancecomparisonsforR-Square						
Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.9672	0.9467	0.9174	0.8999	0.8544	0.8197
Nifty 50	0.9461	0.9165	0.8954	0.8542	0.8192	0.7615
SBIN	0.9494	0.9154	0.8926	0.8762	0.8462	0.8164
ICICI	0.9572	0.9286	0.9051	0.8725	0.8246	0.7916
HDFC	0.9408	0.9358	0.9027	0.8726	0.8291	0.8165
MSFT	0.9437	0.9248	0.9027	0.871	0.8389	0.8034

Table12:TestingperformancecomparisonsforR-Square						
Methods	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.9437	0.9294	0.9027	0.8834	0.8564	0.8164
Nifty 50	0.9601	0.9468	0.9121	0.8598	0.8262	0.8062
SBIN	0.9785	0.9564	0.9256	0.8718	0.8302	0.7861
ICICI	0.9495	0.9387	0.8836	0.8591	0.8261	0.7864
HDFC	0.9782	0.9527	0.9293	0.8901	0.8519	0.7909
MSFT	0.9467	0.9325	0.9027	0.8852	0.8561	0.8259

Results analysis: Phase-II

The results analysis: Phase 2 uses the DELM for predicting the stock market price which is used technical indicator for inputs to the DELM.The DWM method is used to connect weights and bias of ELM for enhancing the performance.The present sub-section discusses the abilityof the developed DELM method.Tables 13, 15,17, 19, and 21 show the training performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively. Tables 14,16,18,20,and 22 shows the testing performance of MSE,RMSE,MAE,MAPE, and R-Square values, respectively.

Table13:Training Performance Comparisons for MSE							
Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S&P	0.000628	0.000738	0.000843	0.001291	0.00482	0.006293	0.009061
Nifty 50	0.001024	0.000129	0.001365	0.001517	0.001738	0.001995	0.002155
SBIN	0.000792	0.000875	0.000937	0.001045	0.001591	0.001836	0.002067
ICICI	0.000596	0.000758	0.000863	0.000983	0.001135	0.001455	0.001864
HDFC	0.000552	0.000691	0.000821	0.000973	0.001847	0.002851	0.003195
MSFT	0.000587	0.000653	0.000694	0.000792	0.000984	0.001587	0.001918

Table14:Testing Performance comparisons for MSE							
Methods	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S&P	0.000959	0.00105	0.00122	0.00294	0.00346	0.00598	0.00718
Nifty 50	0.00369	0.00582	0.00768	0.00892	0.01029	0.01529	0.01989
SBIN	0.000479	0.00068	0.000865	0.000942	0.001191	0.001395	0.001759
ICICI	0.000356	0.00048	0.000658	0.000893	0.001221	0.001426	0.001852
HDFC	0.000489	0.00059	0.000798	0.000931	0.001194	0.001352	0.001698
MSFT	0.00467	0.00061	0.00695	0.00749	0.00897	0.01099	0.0201

Table15:Training Performance comparisons for RMSE							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.02505	0.02716	0.02903	0.03593	0.06942	0.07932	0.09518
Nifty 50	0.03253	0.01135	0.03694	0.03894	0.04168	0.04466	0.04642
SBIN	0.02814	0.02958	0.03061	0.03232	0.03988	0.04284	0.04546
ICICI	0.02441	0.02753	0.02937	0.03135	0.03368	0.03814	0.04317
HDFC	0.02349	0.02628	0.02865	0.03119	0.04297	0.05339	0.05652
MSFT	0.02422	0.02555	0.02634	0.02814	0.03136	0.03983	0.04379

Table16:Testing performance comparisons for RMSE							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.03096	0.0324	0.03492	0.05422	0.05882	0.07733	0.08473
Nifty 50	0.06074	0.07628	0.08763	0.09444	0.10144	0.12365	0.14103
SBIN	0.02188	0.02607	0.02941	0.03069	0.03451	0.03735	0.04194
ICICI	0.01886	0.0219	0.02565	0.02988	0.03494	0.03776	0.04303
HDFC	0.02211	0.02429	0.02824	0.03051	0.03455	0.03677	0.0412
MSFT	0.06833	0.02469	0.08336	0.08654	0.09471	0.10483	0.14177

Table17:Training Performance comparisons for MAE							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.0069	0.0079	0.0095	0.0106	0.0381	0.0451	0.0621
Nifty 50	0.007	0.0084	0.0092	0.0192	0.0281	0.041	0.0515
SBIN	0.0045	0.0051	0.0059	0.00631	0.0072	0.0095	0.0103
ICICI	0.0045	0.0058	0.0069	0.0081	0.0172	0.0377	0.0412
HDFC	0.0052	0.0063	0.0072	0.0079	0.0085	0.0093	0.01016
MSFT	0.0055	0.0067	0.0075	0.0084	0.0095	0.0101	0.0115

Table18:Testing Performance comparisons for MAE							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.0098	0.0102	0.0106	0.0119	0.0125	0.0141	0.0152
Nifty 50	0.0652	0.0752	0.0886	0.0938	0.1022	0.1256	0.1495
SBIN	0.0115	0.0119	0.0124	0.0142	0.0172	0.0199	0.0208
ICICI	0.0099	0.0122	0.0153	0.0291	0.0315	0.0515	0.0821
HDFC	0.0134	0.0138	0.0145	0.0156	0.0176	0.0181	0.0201
MSFT	0.0099	0.0143	0.0127	0.0372	0.0511	0.0676	0.0859

Table19:Training performance comparisons for MAPE							
Methods	**DELM-H**	**DELM-T**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.0016	0.0024	0.0035	0.0059	0.0069	0.0088	0.0105
Nifty 50	0.0064	0.0079	0.0092	0.0102	0.0221	0.0281	0.0315
SBIN	0.0029	0.0046	0.0056	0.0064	0.0071	0.009	0.011
ICICI	0.0006	0.0008	0.0009	0.0018	0.0026	0.0039	0.009
HDFC	0.0045	0.0057	0.0068	0.0072	0.0079	0.0094	0.0101
MSFT	0.0053	0.0059	0.0063	0.0071	0.0078	0.0099	0.0105

Table20:Testing performance comparisons for MAPE							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.0063	0.0068	0.0072	0.008	0.0086	0.0098	0.0095
Nifty 50	0.0049	0.0053	0.0065	0.0078	0.0086	0.0094	0.0105
SBIN	0.0024	0.0031	0.0035	0.0051	0.0072	0.0099	0.0109
ICICI	0.0025	0.0037	0.0041	0.0067	0.0098	0.0139	0.0193
HDFC	0.0026	0.0039	0.0055	0.0069	0.0081	0.0095	0.0111
MSFT	0.0056	0.0061	0.0065	0.0076	0.0081	0.0095	0.0112

Table21:Training performance comparisons for R-Square							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.9762	0.9672	0.9467	0.9174	0.8999	0.8544	0.8197
Nifty 50	0.9624	0.9461	0.9165	0.8954	0.8542	0.8192	0.7615
SBIN	0.9628	0.9494	0.9154	0.8926	0.8762	0.8462	0.8164
ICICI	0.9686	0.9572	0.9286	0.9051	0.8725	0.8246	0.7916
HDFC	0.9652	0.9408	0.9358	0.9027	0.8726	0.8291	0.8165
MSFT	0.9541	0.9437	0.9248	0.9027	0.871	0.8389	0.8034

Table22:Testing performance comparisons for R-Square							
Methods	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S&P	0.9539	0.9437	0.9294	0.9027	0.8834	0.8564	0.8164
Nifty 50	0.9662	0.9601	0.9468	0.9121	0.8598	0.8262	0.8062
SBIN	0.9954	0.9785	0.9564	0.9256	0.8718	0.8302	0.7861
ICICI	0.9622	0.9495	0.9387	0.8836	0.8591	0.8261	0.7864
HDFC	0.9866	0.9782	0.9527	0.9293	0.8901	0.8519	0.7909
MSFT	0.9621	0.9467	0.9325	0.9027	0.8852	0.8561	0.8259

Result analysis:Phase -III

The results analysis: Phase III uses sentiment analysis for predicting the stock market price based on customer sentiment.The CNN algorithm is used to classify the usercomments into bullish/bearish.The Third phase of research work uses both technical indicators and the sentiment of the user as input to the developed DELM is called S-DELM.The present sub-section discusses the ability of the developed S-DELM method.Tables 23, 25, 27, 29, and 31 show the training performance of MSE, RMSE, MAE, MAPE, and R- Square values, respectively.Tables 24, 26, 28, 30, and 32 show the testing performance of MSE, RMSE, MAE, MAPE, and R-Square values, respectively.

Table23:TrainingPerformanceComparisonsforMSE

Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	**0.000521**	**0.000628**	**0.000738**	**0.000843**	**0.001291**	**0.00482**	**0.006293**	**0.009061**
Nifty 50	**0.000894**	**0.001024**	**0.000129**	**0.001365**	**0.001517**	**0.001738**	**0.001995**	**0.002155**
SBIN	**0.000621**	**0.000792**	**0.000875**	**0.000937**	**0.001045**	**0.001591**	**0.001836**	**0.002067**
ICICI	**0.000227**	**0.000596**	**0.000758**	**0.000863**	**0.000983**	**0.001135**	**0.001455**	**0.001864**
HDFC	**0.000302**	**0.000552**	**0.000691**	**0.000821**	**0.000973**	**0.001847**	**0.002851**	**0.003195**
MSFT	**0.000487**	**0.000587**	**0.000653**	**0.000694**	**0.000792**	**0.000984**	**0.001587**	**0.001918**

Table24:TestingPerformancecomparisonsforMSE

Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	**0.00084**	**0.000959**	**0.00105**	**0.00122**	**0.00294**	**0.00346**	**0.00598**	**0.00718**
Nifty 50	**0.00111**	**0.00369**	**0.00582**	**0.00768**	**0.00892**	**0.01029**	**0.01529**	**0.01989**
SBIN	**0.000191**	**0.000479**	**0.00068**	**0.000865**	**0.000942**	**0.001191**	**0.001395**	**0.001759**
ICICI	**0.000127**	**0.000356**	**0.00048**	**0.000658**	**0.000893**	**0.001221**	**0.001426**	**0.001852**
HDFC	**0.000199**	**0.000489**	**0.00059**	**0.000798**	**0.000931**	**0.001194**	**0.001352**	**0.001698**
MSFT	**0.00156**	**0.00467**	**0.00061**	**0.00695**	**0.00749**	**0.00897**	**0.01099**	**0.0201**

Table25:TrainingPerformancecomparisonsforRMSE

Methods	**S-DELM**	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.02282	0.02505	0.02716	0.02903	0.03593	0.06942	0.07932	0.09518
Nifty 50	0.02989	0.03253	0.01135	0.03694	0.03894	0.04168	0.04466	0.04642
SBIN	0.02491	0.02814	0.02958	0.03061	0.03232	0.03988	0.04284	0.04546
ICICI	0.01506	0.02441	0.02753	0.02937	0.03135	0.03368	0.03814	0.04317
HDFC	0.01737	0.02349	0.02628	0.02865	0.03119	0.04297	0.05339	0.05652
MSFT	0.02206	0.02422	0.02555	0.02634	0.02814	0.03136	0.03983	0.04379

Table26:TestingperformancecomparisonsforRMSE

Methods	**S-DELM**	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.02898	0.03096	0.0324	0.03492	0.05422	0.05882	0.07733	0.08473
Nifty 50	0.03331	0.06074	0.07628	0.08763	0.09444	0.10144	0.12365	0.14103
SBIN	0.01382	0.02188	0.02607	0.02941	0.03069	0.03451	0.03735	0.04194
ICICI	0.01126	0.01886	0.0219	0.02565	0.02988	0.03494	0.03776	0.04303
HDFC	0.0141	0.02211	0.02429	0.02824	0.03051	0.03455	`	0.0412
MSFT	0.03949	0.06833	0.02469	0.08336	0.08654	0.09471	0.10483	0.14177

Table27:TrainingPerformancecomparisonsforMAE

Methods	**S-DELM**	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.0034	0.0069	0.0079	0.0095	0.0106	0.0381	0.0451	0.0621
Nifty 50	0.0058	0.007	0.0084	0.0092	0.0192	0.0281	0.041	0.0515
SBIN	0.0027	0.0045	0.0051	0.0059	0.00631	0.0072	0.0095	0.0103
ICICI	0.0029	0.0045	0.0058	0.0069	0.0081	0.0172	0.0377	0.0412
HDFC	0.0034	0.0052	0.0063	0.0072	0.0079	0.0085	0.0093	0.01016
MSFT	0.0043	0.0055	0.0067	0.0075	0.0084	0.0095	0.0101	0.0115

Table28:TestingPerformancecomparisonsforMAE

Methods	**S-DELM**	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.0079	0.0098	0.0102	0.0106	0.0119	0.0125	0.0141	0.0152
Nifty 50	0.0308	0.0652	0.0752	0.0886	0.0938	0.1022	0.1256	0.1495
SBIN	0.0101	0.0115	0.0119	0.0124	0.0142	0.0172	0.0199	0.0208
ICICI	0.0081	0.0099	0.0122	0.0153	0.0291	0.0315	0.0515	0.0821
HDFC	0.0117	0.0134	0.0138	0.0145	0.0156	0.0176	0.0181	0.0201
MSFT	0.0096	0.0099	0.0143	0.0127	0.0372	0.0511	0.0676	0.0859

Table29:TrainingperformancecomparisonsforMAPE

Methods	**S-DELM**	**DELM-H**	**DELM-T**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.0004	0.0016	0.0024	0.0035	0.0059	0.0069	0.0088	0.0105
Nifty 50	0.0058	0.0064	0.0079	0.0092	0.0102	0.0221	0.0281	0.0315
SBIN	0.0004	0.0029	0.0046	0.0056	0.0064	0.0071	0.009	0.011
ICICI	0.0004	0.0006	0.0008	0.0009	0.0018	0.0026	0.0039	0.009
HDFC	0.0003	0.0045	0.0057	0.0068	0.0072	0.0079	0.0094	0.0101
MSFT	0.0006	0.0053	0.0059	0.0063	0.0071	0.0078	0.0099	0.0105

Table30:TestingperformancecomparisonsforMAPE

Methods	**S-DELM**	**DELM-T**	**DELM-H**	**GAELM**	**KELM**	**ELM**	**SVM**	**BPNN**
S &P	0.0058	0.0063	0.0068	0.0072	0.008	0.0086	0.0098	0.0095
Nifty 50	0.0037	0.0049	0.0053	0.0065	0.0078	0.0086	0.0094	0.0105
SBIN	0.0016	0.0024	0.0031	0.0035	0.0051	0.0072	0.0099	0.0109
ICICI	0.0011	0.0025	0.0037	0.0041	0.0067	0.0098	0.0139	0.0193
HDFC	0.0011	0.0026	0.0039	0.0055	0.0069	0.0081	0.0095	0.0111
MSFT	0.0014	0.0056	0.0061	0.0065	0.0076	0.0081	0.0095	0.0112

Table31:TrainingperformancecomparisonsforR-Square								
Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.9998	0.9762	0.9672	0.9467	0.9174	0.8999	0.8544	0.8197
Nifty 50	0.9997	0.9624	0.9461	0.9165	0.8954	0.8542	0.8192	0.7615
SBIN	0.9999	0.9628	0.9494	0.9154	0.8926	0.8762	0.8462	0.8164
ICICI	0.9998	0.9686	0.9572	0.9286	0.9051	0.8725	0.8246	0.7916
HDFC	0.9956	0.9652	0.9408	0.9358	0.9027	0.8726	0.8291	0.8165
MSFT	0.9893	0.9541	0.9437	0.9248	0.9027	0.871	0.8389	0.8034

Table32:TestingperformancecomparisonsforR-Square								
Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM	SVM	BPNN
S &P	0.9958	0.9539	0.9437	0.9294	0.9027	0.8834	0.8564	0.8164
Nifty 50	0.9983	0.9662	0.9601	0.9468	0.9121	0.8598	0.8262	0.8062
SBIN	1	0.9954	0.9785	0.9564	0.9256	0.8718	0.8302	0.7861
ICICI	0.9959	0.9622	0.9495	0.9387	0.8836	0.8591	0.8261	0.7864
HDFC	1	0.9866	0.9782	0.9527	0.9293	0.8901	0.8519	0.7909
MSFT	0.9861	0.9621	0.9467	0.9325	0.9027	0.8852	0.8561	0.8259

Table33:Trainingcomputationtime						
Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM
S&P	132.85	135.94	149.27	158.25	0.0418	0.0587
Nifty 50	140.94	142.94	150.71	167.84	0.0618	0.0637
SBIN	135.94	140.51	146.94	155.39	0.0527	0.0539
ICICI	138.52	143.27	146.73	150.86	0.0505	0.0552
HDFC	138.64	142.68	145.72	148.55	0.0559	0.0608
MSFT	134.67	139.81	140.31	143.95	0.0517	0.0495

Table34:Testingcomputationtime						
Methods	S-DELM	DELM-T	DELM-H	GAELM	KELM	ELM
S&P	0.0146	0.0267	0.0289	0.0348	0.001582	0.001907
Nifty 50	0.0128	0.0253	0.0263	0.0294	0.001957	0.002158
SBIN	0.0142	0.0268	0.0297	0.0318	0.001658	0.001895
ICICI	0.0184	0.0237	0.0253	0.0287	0.001837	0.002067
HDFC	0.0192	0.0255	0.0271	0.0302	0.001737	0.001995
MSFT	0.0183	0.0239	0.0247	0.0299	0.001673	0.001871

Compared with standard BPNN, SVM, ELM, KELM, GA-ELM, and DELM, the R^2 of proposed S-ELM is improved by 16.19 %, 12,295 %, 9.47 %, 6.93 %, 3,24 % on average, respectively.In conclusion,the suggested scheme regularly obtains the highest accuracy,the lowest time offset, and the closest predictive value when predicting the stock market using ELM in conjunction with the sentiment index and DWM.

Few studies concentrate on the precise price and timeliness of stocks, even though many have examined the rise and fall of equities. Accurate and timely stock price forecasting is essential for both investor decision-making and the stability of the national economy. It will make sense to support the steady, sustainable growth of the economy with more timely and appropriate regulation, timely and accurate stock price predictions, and sound stock market guidance. ELM is often chosen for its fast training speed, making it suitable for large-scale datasets and real-time applications. The efficient computation time allows ELM to handle largevolumes of data more quickly than someother machine learning algorithms.Hence, the present research work takes computation time also for performance comparisons.Tables 33 and 34 and Figures 32 and 33 show the computation time for all compared methods and respective datasets.Hence, the developed method produces a low computation time when compared with some variants of ELM with SI and a high computational time when compared with

conventional ELM and KELM.

VII.Conclusion

The present research work proposes a sentiment analysis-based ELM stock market prediction model. Specifically, the sentiment index is utilized to account for the emotional inclination of the investor. CNN is used the classify user comments into bullish or bearish which is used for calculated sentiment index.Both sentiment index and technical indicators are considered for inputs to the prediction method.Secondly, DWM optimizes the ELM- based model by breaking down the intricate stock price sequence into simpler and more predictable sequences.DWM is used to optimize connection weights and bias of ELM. Experiments were out on the six datasets to confirm that the suggested method performs as expected.The experimental results demonstrate that the suggested system consistently performs better than the comparative schemes in three key areas: reduced time offset, higher rise and fall classification accuracy, and closer predicted closing price.

VIII.Scope of further research

The usage of semi-supervised models, for instance, can help reduce the amount of stock review datasets needed for sentiment index computations and emotional classification. On the other hand, capturing non-linear correlations and patterns in data is an area in which deep learning models thrive.When it comes to stock market prediction, deep learning models might perform better than shallow neural networks or traditional linear models because the correlations between input data and stock prices can be quite dynamic and non-linear.

IX. List of Publications

1. “Enhanced Extreme Learning Machine Algorithm with Deterministic Weight Modification for Investment Decision on Indian Stocks”, in *2022 3rd International Conference on Smart Electronics and Communication (ICOSEC)*, 2022: IEEE, pp. 1409-1414.

2. “A systematic review on artificial neural networks for stock market prediction”, in *International conference on emerging trends in multi disciplinary approaches in higher education (ICON)*,2022 .ISBN: 978-81-929698-8-6,pp.123-127

3. “Extreme Learning Machine Algorithm with Deterministic Weight Modification for investment Decision based on sentiment Analysis” in National Conference on Multidisciplinary for Sustainable Innovations (NCMRSI)2023:ISBN-978-81-931101-6-4,pp.24-32.

4. “Modified Extreme Learning Machine algorithm with deterministic Weight Modification for investment Decisions based on Sentiment Analysis” published in Recent advances in Computer Science and Communications ISSN(Print):2666-558,ISSN(Online):2666-2566 ,vol 16, issue 8,2023 DOI:10.2174/2666255816666230815121119

5. “The Deterministic weight modification based extreme learning machine for stock price prediction” Published in Recent patents on Engineering ISSN (Print): 1872-2121 ISSN (Online): 2212-4047 Published on: 04 December, 2023 DOI: 10.2174/0118722121268858231111180830

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